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Dynamics of Affordance Actualization

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Abstract

The actualization of affordances can often be accomplished in numerous, equifinal ways. For instance, an individual could discard an item in a rubbish bin by walking over and dropping it, or by throwing it from a distance. The aim of the current study was to investigate the behavioral dynamics associated with such metastability using a ball-to-bin transportation task. Using time-interval between sequential ball-presentation as a control parameter, participants transported balls from a pickup location to a drop-off bin 9m away. A high degree of variability in task-actualization was expected and found, and the Cusp Catatrophe model was used to understand how this behavioral variability emerged as a function of hard (time interval) and soft (e.g. motivation) task dynamic constraints. Simulations demonstrated that this two parameter state manifold could capture the wide range of participant behaviors, and explain how these behaviors naturally emerge in an under-constrained task context.

Keywords: affordances; dynamic systems; cusp catastrophe; dynamic modeling; simulations; constraints;

Introduction

Reorganizing one's activity in relation to changing task demands is a ubiquitous aspect of everyday life and is often required to ensure task success. In order to solve everyday perception-action tasks, human (and animal) behavior is functionally (re)organized in relation to the affordances that define a given task context. Here, the term *affordance* simply refers to the action possibilities that characterize a given agent-environment system (Gibson, 1979).

Starting with Warren's (1984) seminal work on the perception of climb-ability, affordance perception research has demonstrated that affordances are defined by dimensionless ratios (termed pi-numbers) that capture the intrinsic, or body-scaled "fit" between the relevant aspects of an environmental surface or object and an intentional agent's perception-action capabilities (i.e. effectivities). For instance, a stair riser is perceived to afford (comfortable) climbing if the ratio of the perceivers leg-length with respect to the height of the riser is less than approximately $\pi = .85$.

Similar body-scaled ratios are known to define a wide range of action possibilities, from the stand-ability and sit-ability of surfaces (e.g., Fitzpatrick, Carello, Schmidt & Corey, 1994; Mark, 1987), to the pass-through-ability of apertures (Warren & Whang, 1987), and the reach-ability and grasp-ability of objects (e.g., Carello, Grosofsky, Reichel & Solomon, 1989; Cesari & Newell, 1999; Richardson, Marsh & Baron, 2007). In each case, this research has demonstrated how individuals correctly detect affordance boundaries (i.e., the boundary between when an action is or is not possible) by means of intrinsic body-scaled information (e.g., eye-height information) and organize or reorganize their behavioral activity accordingly (Carello et al., 1989). For instance, individuals are able to correctly perceive when an object is reach-able or not by extending their arm when seated, or by bending their torso and extending their arm, or by standing up and walking over to the object and organize their behavior accordingly.

It is important to appreciate, however, that in most task contexts the different ways in which an affordance can be actualized are not organizationally discrete, but overlap. For instance, an object that is reachable by extending the arm, is also often reachable by bending the torso and extending the arm. Similarly, an object that is graspable with one hand, is also likely graspable with two hands. Furthermore, a small, light ball could be gripped with the fingers or grasped with the whole hand, and then carried or thrown to its final destination. In this sense, afforded task goals often entail a nested structure of multiply realizable action possibilities.

In dynamical systems terms, a nested affordance structure corresponds to a multi-stable system, whereby two or more states or modes of behavioral order are simultaneously stable (and could be actualized). Regarding the perception and actualization of nested affordances, a sign of multi-stability is *hysteresis* (Kelso, 1995; Turvey, 1990). This occurs when an individual transitions between two different behavioral modes or states at different body-scaled ratios depending on its history of previous performance. For example, an individual will typically transition from one-hand to two-hand grasping at a larger arm-span/object-size ratio (i.e., π = .8) as object size is increased, compared to when transitioning from two-hand to one-hand grasping (i.e., π = .65) as object size is decreased (e.g., Frank, Richardson, Lopresti-Goodman & Turvey, 2009; van der Kamp, Savelsbergh & Davis, 1998). Although hysteresis has been observed in numerous affordance studies, other dynamic patterns of behavior have also been observed. For instance, in many task contexts individuals exhibit a fixed or *critical point transition* between different affordances or modes of affordance actualization. That is, individuals exhibit a *nonlinear phase transition* between different affordances or behavioral modes at the same body-scaled ratio irrespective of whether it is scaled up or down (Richardson et al., 2007; van der Kamp, et al., 1998). Enhanced contrast or *negative hysteresis* has also been observed and is defined by individuals transitioning between different behavioral modes in a prospective or anticipatory manner (Richardson et al., 2007; Lopresti-Goodman et al. 2013). While these transitions show distinct changes in the actualization of an affordance over time, they are still stable solutions in terms of the task goal, or *metastable*. For example, in order to successfully grasp planks as plank size is increased, a transition (that varies inter-individually) between one-handed and two-handed grasping is necessary to maintain the task goal. Of course, fixed state behavior has also been observed, whereby an individual will enact the same affordance even if other behavioral modes are more effective or stable. For example, in an object grasping task a pair of individuals may choose to pick up objects together, even when it is more efficient and stable to pick up smaller objects separately (Richardson et al., 2007).

Of particular relevance here, is that the varied manner in which individuals are known to actualize a given affordance or transition between different affordances implies that affordance actualization is not determined by body-scaled ratios alone, but rather is determined by a more complex set of behavioral and contextual constraints. For example, the amount of time an individual has to perform a given task, an individual's motivation, and an individual's perceived ability for achieving task success are known to play a determining role in how a particular affordance is actualized (e.g., Lopresti-Goodman, Richardson, Marsh, Carello, & Baron, 2007; Wilson, Weightman, Bingham, & Zhu, 2016).

In an attempt to better understand how differing task constraints influence affordance actualization, Fajen (2007) has proposed a distinction between hard versus soft constraints. Briefly stated, hard constraints are constraints that define a clear line between task success and failure. For example, when driving there is a minimum distance in which a driver would need to start braking in order to avoid colliding into a car stopped in front of them. The boundary between stopping and colliding thus corresponds to a hard task constraint, and if crossed will result in rather dramatic and potentially deadly task failure. However, even in this situation, successfully stopping could entail breaking close to this hard constraint or well before it. Of course, what determines which successful type of breaking behavior a driver chooses to actualize will depend on many different factors, such as the time of day, mood, or the degree to which a given driver prefers a large or small margin of safety. It is these kinds of latter constraints that correspond to soft constraints (Fajen, 2007; also see Harrison, Turvey & Frank, 2016).

Current study

The aim of the current study was to examine and model the effects of hard and soft constraints on affordance actualization, for a ball-to-bin transportation task. Of particular interest was the role that temporal constraints play on shaping the behavioral dynamics of an under- or softly-constrained affordance actualization task. To achieve this, individuals were instructed to transport balls from a starting location to a target bin located 9 meters away. The interval between sequentially presented balls was manipulated by increasing or decreasing number of seconds between 2 and 14 (or vice versa) in 1 second steps every fourth ball. Importantly, individuals could complete the ball-to-bin transportation task in any way they wished; by walking/running and dropping the balls into the target bin or by throwing the balls into the bin from whatever distance they liked. Of interest was the distance that individuals chose to move prior to releasing the ball and the degree to which time-interval, as a control parameter, operated as a constraint on the observed behavioral dynamics.

Given the under-constrained nature of the task and the fact that it was impossible for individuals to achieve complete task success, the expectation was to observe a variety of behavioral dynamics. More specifically, using distance moved prior to attempting to throw the ball into the bin as the dependent variable, the expectation was that participants would exhibit one of four general classes of behavior as time-interval was increased or decreased across a continuous sequence of 52 balls: (I) fixed large distance moved (essentially always walking or running nearly the complete distance to the target bin); (II) fixed small distance moved (essentially always throwing from the ball pickup location); (II) gradual transition from large to small distance moved (or vice versa); and (IV) a non-linear transition between large and small distance moved.

It was also expected that the variation in the behavioral dynamics observed could be modeled using a two parameter, bifurcation or catastrophe model (namely, the cusp catastrophe), in which the first parameter was represented by time interval and the second represented the collective approximation of the unknown soft constraints that influenced a given individual's behavioral dynamics. Before explicating this modeling endeavor however, the method and data analysis employed for the experimental study is detailed.

Method

Participants

Sixty-nine undergraduates from the University of Cincinnati participated in the experiment for partial course credit.

Materials

At the starting area, seven-inch plastic playpen balls were put through an angled PVC pipe (marked '4' in Figure 1) that protruded into the pick-up area located on a wooden table (marked '3', dimensions: 40cm wide, and 26.5cm deep). The mouth of the PVC pipe extended back through an opaque curtain (marked '2') and a large wooden bin (marked '1', dimensions: 110cm wide, 55cm deep, and 120cm high) was positioned at nine meters from the back edge of the ball pickup area. A computer program was used to visually signal an experimenter ('E') positioned behind the pickup location curtain (2) when to release the balls (one by one). A video-camera was used to record participants' ('P') movements and actions throughout the experiment.

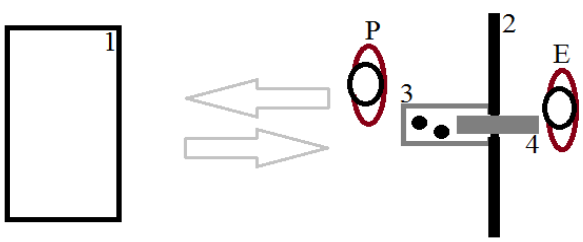

Figure 1: General experimental setup.

Task and Procedure

Participants were told that the task involved transporting plastic playpen balls from a pickup area to a wooden bin located on the other side of the laboratory room. They were instructed they could only use one ball at a time and that the task was to get the balls into the bin, while at the same time not letting multiple balls stack up at the pickup location. They were told that the time between ball presentations would change from fast to slow or slow to fast (depending on sequence condition). They were also told that if they drop a ball accidentally then it could be picked up, however, if there was an attempt to get the ball into the bin but they missed, then they should ignore it and move on to the next one. Finally, they were instructed to solve the task in any way they liked as long as they followed the rules. (There were no consequences if rules were broken, and no incentive was given for performance).

Participants completed two trial series, with each series including the sequential presentation of fifty-two balls. Thirty-five participants started their first series at an increasing rate: beginning with a 14 second interval of ball presentation, this interval was decreased by 1 second after four balls down to 2 seconds (i.e., four balls were presented sequentially at each time interval). A small break was provided and then the second series began with the control parameter scaled in the reverse direction (i.e., from 2 to 14 seconds). The other thirty-four participants completed these same two trial sequences in the reverse order (i.e., 2 to 14 second sequence, followed by the 14 to 2 second sequence).

Data Analysis and Behavioral Classification

The distance that participants moved prior to releasing (throwing or dropping) the ball was determined from the video recordings, along with task success (i.e., whether participants successfully got the ball into the bin or not). Although not reported here, the number of balls left within the pickup area at the time that the participant was attempting to get their current ball in was also recorded.

The movement distances were analyzed using Matlab 2016a (MathWorks, MA), with the behavior exhibited by participants in each temporal series (i.e., 2 to 14 second and 14 to 2 second series) graphically classified into one of four different types of dynamics (see below for more details). Prior to classification, the movement distances were averaged over each change in time interval, i.e. the average distance moved prior to releasing the ball was calculated over the four balls that had a fourteen second interval, then the average distance moved prior to releasing the ball was calculated over the four balls within thirteen second intervals, etc. This resulted in thirteen averaged movement distances for each 52-ball sequence. From these behavioral time-series, two descriptive statistics, namely mean distance moved (D_m) and largest change in distance moved across a change in time interval (ΔD; i.e. the maximum of the differentiated 13-point behavioral time-series) were used to classify each behavioral time series as follows:

- Stable (fixed) small distance (***stD***$_{small}$) moved, whereby participants essentially always throw the ball from the pickup location or near the pickup location. More specifically, $D_m < 4.8$ meters and $\Delta D < 1.58$ meters.
- Stable (fixed) large distance (***stD***$_{large}$) moved, whereby participants essentially always moved across nearly the complete distance to the target bin prior to releasing the ball. More specifically, $D_m > 4.8$ meters and $\Delta D < 1.58$ meters.
- Gradual change (phase transition) in distance (***ptD***$_{gradual}$) moved, whereby participants gradually increased or decreased the distance as time interval decreased or increased, respectively (i.e., an inverse relationship between distance moved and time interval). More specifically, $1.58 < \Delta D < 3.8$ meters.
- Nonlinear change (phase transition) in distance (***ptD***$_{nonlinear}$) moved whereby participants exhibited a large

or nonlinear change in distance moved across a small change in interval. More specifically, $\Delta D > 3.8$ meters.

Example time-series of each behavioral type are provided in Figure 2 for both increasing and decreasing interval sequences.

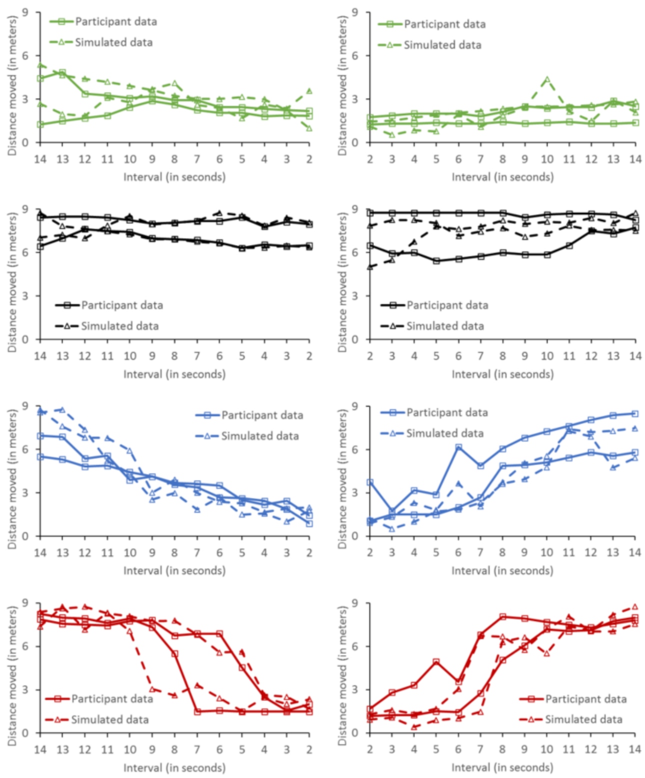

Figure 2: Two examples each of participant (full line, square markers) and simulated (dotted line, triangle markers) trajectories: **stD_{small}** trajectories (top), **stD_{large}** (second), **$ptD_{gradual}$** (third) and **$ptD_{nonlinear}$** (bottom).

Modeling and Simulation

The possible emergence of the above four types of behavioral dynamics was modeled using a two-parameter task manifold defined by the Cusp Catastrophe (Thom, 1975) equation

$$\dot{x} = a + bx - x^3 \tag{1}$$

where x represented that state or dependent variable, i.e., the distance (rescaled) moved prior to releasing or throwing the ball, the parameter a represented (normalized) time interval from (-2.5 = 2 seconds to +2.5 = 14 seconds), and the parameter b represented the collective state of (unknown) soft constraints that might be influencing a participant's behavior at any point during the task (i.e., motivation, intention, perceived ability, learned helplessness, etc.). The manifold in Figure 3 represents the fixed points of x, for different parameter settings of a and b. That is, each point on the manifold can be understood as representing the distance moved prior to releasing the ball for each (a,b) setting, where x is rescaled (normalized) as a function of b (e.g., from -2 = 0 meters moved to +2 = 9 meters walked when b = 2.8 and from -1 = 0 meters moved to +1 = 9 meters walked when b = -1.8).

As can be seen in Figure 3, this manifold includes both mono-stable and bi-stable (multi-stable) regions and predicts the same four patterns of behavioral dynamics defined above depending on the values of a and b. More specifically, as a is scaled up or down, larger values of b can result in behavioral trajectories qualitatively consistent with **stD_{large}** and **stD_{small}**, depending on the initial condition of x. For $-.5 < b < 3$, however, the manifold predicts varying degrees of **$ptD_{nonlinear}$** type behavior as a (time interval) is scaled up or down. Finally, when $b < -.5$ the manifold predicts **$ptD_{gradual}$** as a (time interval) is scaled up or down.

It is worth noting at this point that Eq. (1) or the Cusp Catastrophe model has been employed to abstractly capture a wide range of natural bifurcation phenomena, including human anxiety and performance, organizational order, decision-making and dating behavior (e.g., Guastello, 1995; Hardy, 1996; Hardy & Fazey, 1987; Richardson, Dale & Marsh, 2014; Tesser, 1980). Typically, the b parameter is fixed and the different behaviors that Eq. (1) can produce are explored by scaling a. In fact, this is how the exemplar trajectories plotted on the manifold in Figure 3 were generated (i.e., by fixing the value of b and then scaling a for a given initial condition x_0). In the current task context, this would be equivalent to assuming that although the soft constraints that influence a participant's behavior might change across trial sequences, they remain fixed over a ball sequence. However, there is no reason to assume that this is the case for the current task, rather it seems more likely that the various soft constraints that influence participant behavior change both during and across sequences. For instance, an individual's motivation or goal intention may have been continuously modulated during the task. Thus, at each interval change (or individual ball), the resulting distance moved may reflect a continuous (or discrete) change in both a and b.

With the latter point in mind, a range of behavioral trajectories were simulated along the cusp catastrophe manifold by scaling a in interval steps consistent with the time interval steps employed in the experimental study (i.e., from 2.5 to -2.5 in 13 steps), as well as scaling b recursively by adding a number from a unimodal random distribution, with a mean of -.6 (when increasing interval, +.6 when decreasing) and a standard deviation of 1.65. The mean of ±.6 was employed as the experimental data revealed that participants had a preference for higher movement (see results section for details). Two sets of 70 trajectories were simulated, with the initial condition x_0 set at +2 for simulation set one and a normal distribution with 50% chance of being above 0 for simulation set two (again inspired by participant behavior). The simulated data that resulted was rescaled to the distances of the real (human) experimental data (~.75 meters to ~8.75 meters).

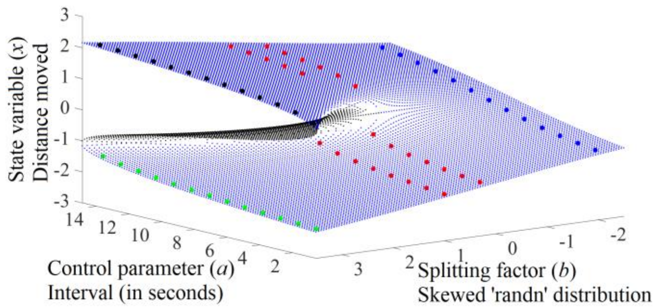

Figure 3: Cusp Catastrophe Model manifold. Blue points represent an exemplar ***ptD**$_{gradual}$* behavioral trajectory. Red points represent two exemplar ***ptD**$_{nonlinear}$* behavioral trajectories. The black and green points represent exemplar ***stD**$_{large}$* and ***stD**$_{small}$* behavioral trajectories, respectively.

Results

As can be seen from an inspection of Figures 2 and 4, and Table 1, participants produced all four of the behavioral dynamics expected. The variability within and across participants and ball sequences is most easily discerned from an inspection of Figure 4, in which the behavioral dynamics classification is plotted as a function of mean distance moved (D_m) and maximum change in distance moved across a change in time-interval (ΔD).

Table 1: Distribution of trajectories per type of data.

Trajectory	Simulated	Actual
stD$_{small}$	8.57%	9.42%
stD$_{large}$	33.57%	35.51%
ptD$_{gradual}$	22.14%	23.91%
ptD$_{nonlinear}$	35.71%	31.16%

The simulated trajectories also produced a comparable set of behavioral trajectories and classifications. Again, this can be seen from an inspection of Figures 2 and 4 and Table 1. The classification system was verified using a K-means Nearest Neighbor (KNN) classifier (in Matlab, with ten number of neighbors, Euclidian distance and squared inverse distance weights) finding 99.28% correspondence between initial classification and KNN classification of real data.

A curve estimation analysis was conducted on the total frequencies of each distance across all data-points, revealing a linear increase in frequency as distance increased (β = .85, $t(34)$ = 9.43, p < .01, where x = distance moved). A two-tailed, bivariate correlation analysis was run to investigate the relationship between distance moved and success (hit) versus failure (miss), revealing a positive association (r = .64, p < .01) in that, as distance moved increased so did the probability of success.

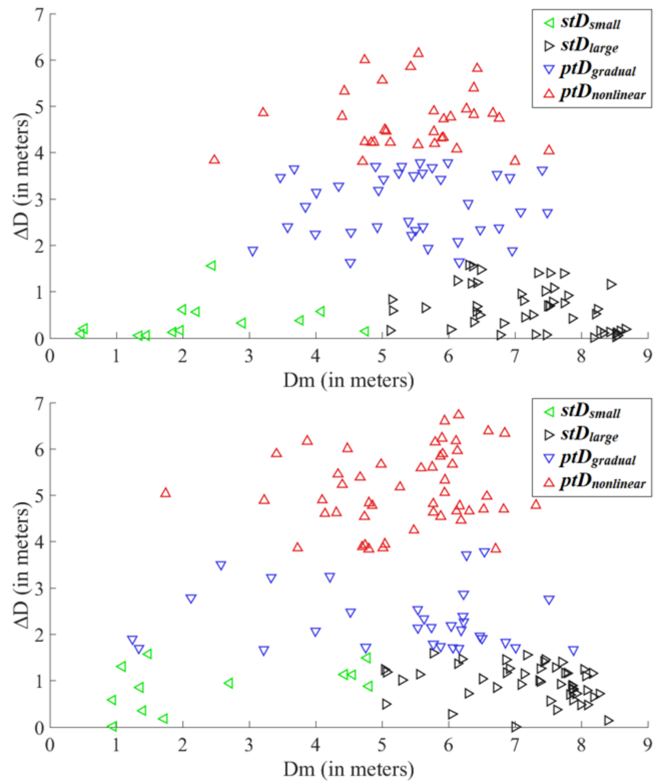

Figure 4: Participant (top) and simulated data (bottom) behavioral classification as a function of mean distance moved (D_m) and maximum change in distance (ΔD).

Discussion

The current study was designed to explore the effects of hard and soft constraints on the manner in which a task goal was actualized. As expected, a variable range of behavioral dynamics was observed, reflecting the under-constrained nature of the task goal. Furthermore, simulations using a two-parameter Cusp Catastrophe manifold illustrated how the wide range of participant behaviors observed naturally emerged due to an under- or softly-constrained task context. That is, by the continuous modulation of soft constraints during ongoing task performance.

The significance of the current findings with regard to understanding human, affordance-based behavior is twofold. First, the current results highlight how both steady state linear and nonlinear behavioral patterns, as well as metastable and transient behavioral patterns, can all result from the same task dynamic, further emphasizing how complex and context sensitive determinism underlies the emergent (re)organization of ongoing human behavior.

Second, the current results illustrate the need for appropriately identifying what and how soft constraints modulate the actualization of nested affordances or multi-stable behavioral modes. While there was no attempt to specifically identify what soft constraints guided task performance in the current study, the experimental and modeling methodology developed here could be employed to identify these constraints in future research. Different hard constraints could be imposed or manipulated, or the saliency of soft constraints within the task context could be explicitly defined. For example, one could introduce the hard (goal) constraint that a participant would fail completely (and need to redo the task) if there is ever more than one ball in the pickup area. This would likely see the elimination of ***stD_{large}*** behavior. Furthermore, if the salience of a soft constraint were also increased, say by adding motivation in terms of a points or monetary reward system that empathized getting balls in the bin, then one would also predict the (near) elimination of ***stD_{small}***, with participants predominately producing ***$ptD_{gradual}$*** or ***$ptD_{nonlinear}$*** behavior.

It is also possible that task success or failure on each ball throw could have modulated the collective motivational state of participants. The general relationship between longer distance and higher success rate speaks to this point, although it does not apply as motivation to all participants equally. (If this were applicable on an individual basis, there would likely be no ***stD_{small}*** trajectories.) However, a confounding variable here is the general preference across the entire dataset for longer distances. The interaction of this preference with the individually different effect of time-interval on distance moved, needs to be examined further in future research.

Acknowledgments

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